From Satellite Images to Vector Representations

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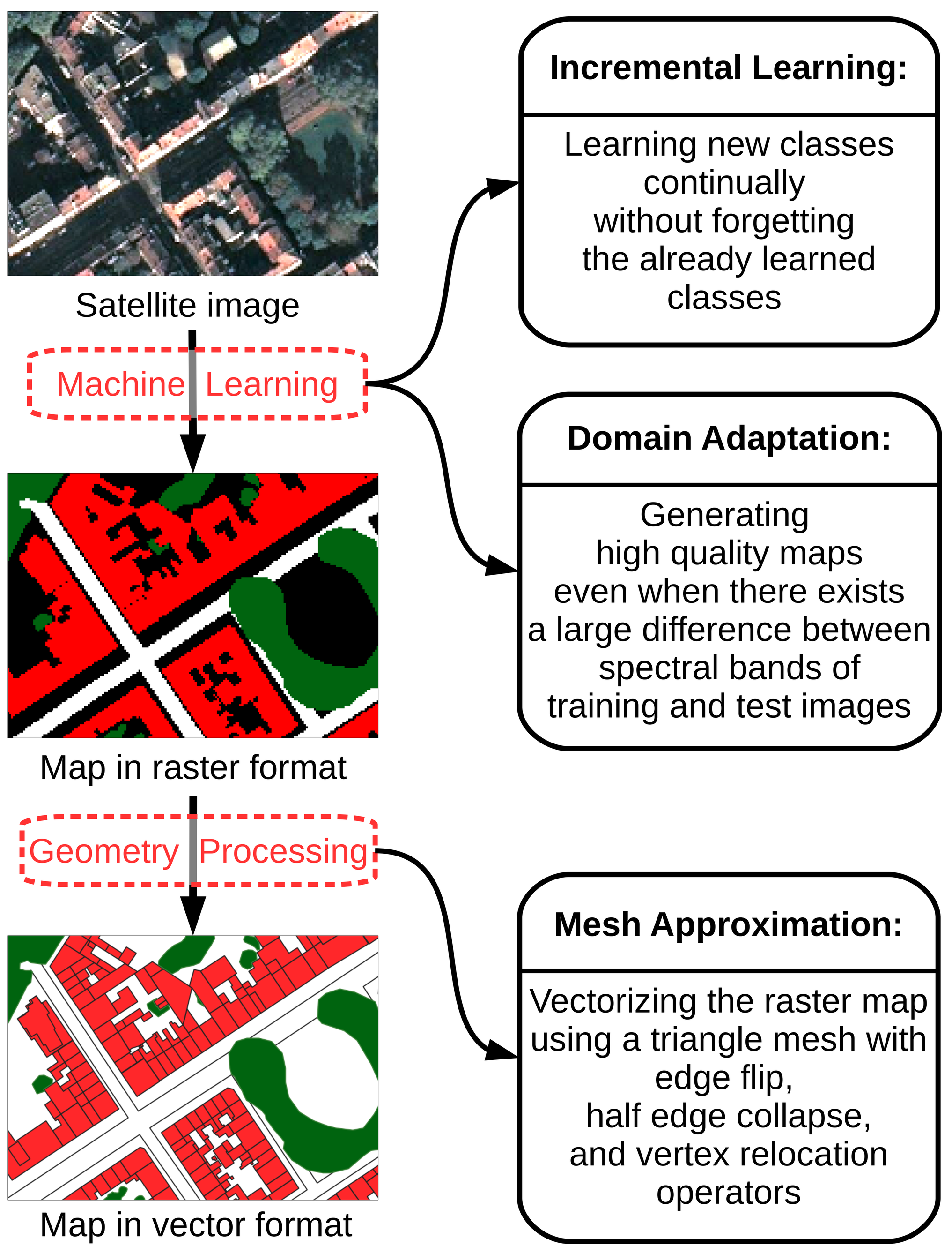
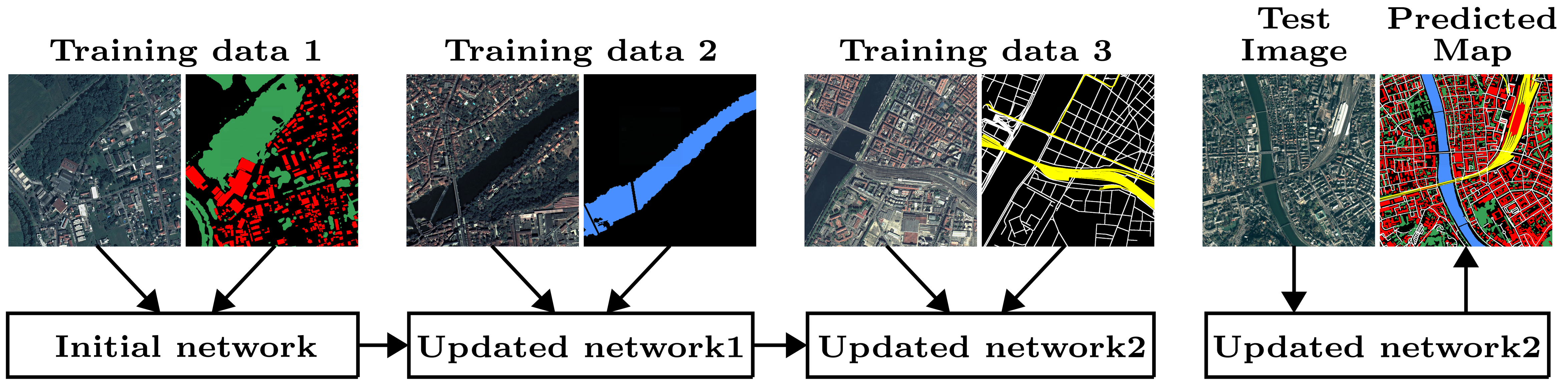
Introduction

One of the most popular challenges in the field of remote sensing is to generate vector representations from satellite images to be included into various Geographic Information System (GIS) applications. One way to generate the aforementioned vector representations is to split this task into two consecutive sub-tasks, where the first one consists in generating pixel-wise maps in raster format using advanced machine learning techniques, and the second one aims at vectorizing the obtained raster map by applying computational geometry methods. We propose novel methods for both sub-tasks.

Overview



Incremental Learning

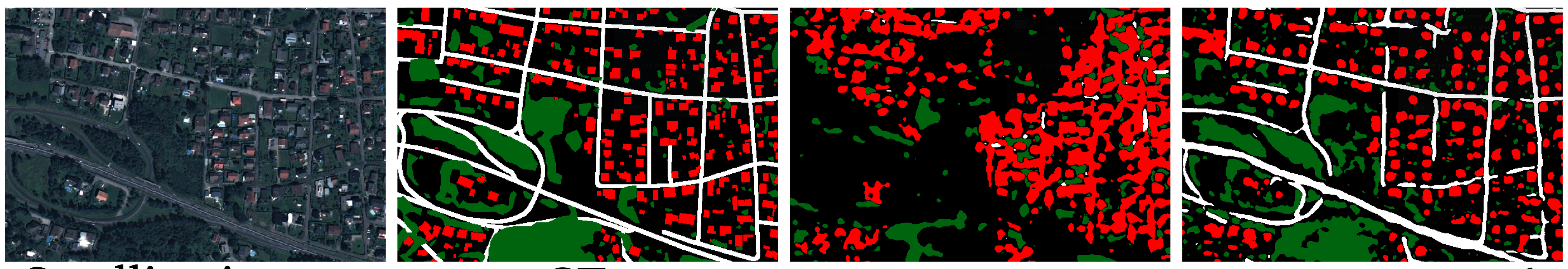


- When new classes are added to the already trained model, the current approaches suffer from catastrophic forgetting (significant performance drop for the previous classes).
- The training phase of our framework [1, 3] has two stages: adaptation and remembering.
- During the adaptation, we use new ground-truth to learn new classes on the current data, and we use the output of the previously trained network to learn old classes from the current data.
- In the remembering phase, we store only a small portion of the previous training data, and we use it to remind the network the learned information for old classes from the previous data.

Domain Adaptation

Bad Ischl | Fake Bad Ischl | Villach | Fake Villach

- When there is a large shift between the spectral bands of training and test images, the existing machine learning models fail to segment the test data.
- We generate fake training images that are semantically exactly the same as the original training images, but whose spectral distribution as close as possible to test images by ColorMapGAN [2].
- We then use the fake training data to fine-tune the model trained on the original training data.

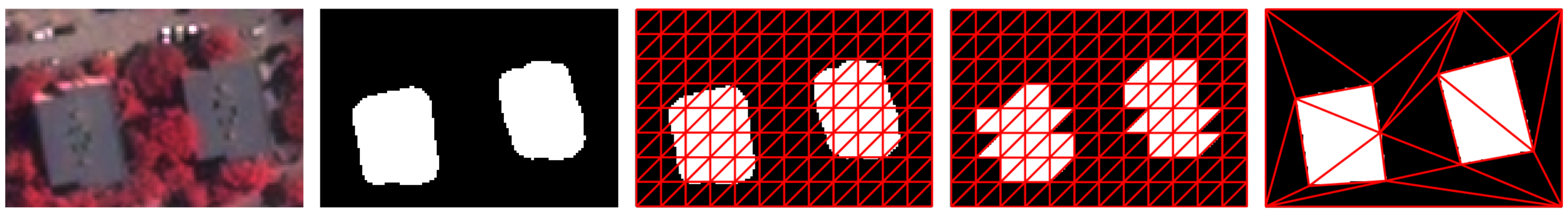


Satellite image | GT | U-net | Our Framework

Conclusions

Incremental Learning: To the best of our knowledge, we propose the first work on incremental learning for semantic segmentation.
Domain Adaptation: The proposed approach is architecturally simple but powerful. We achieve a better performance than the existing approaches in a much shorter period of time.
Mesh Approximation: The approach yields a better accuracy than the simplification algorithms in common GIS softwares, although our method generates significantly less number of vertices.

Mesh Approximation



Satellite image | Segmentation | Initial mesh | Labeled mesh | Optimal mesh

- We transform the initial mesh to the optimal mesh by minimizing an objective function with certain operators [4].
- Our objective function balances between fidelity to the classification map in ℓ_1 norm sense, right angle regularity for polygonized buildings, and the final mesh complexity.
- The operators: edge flip, half edge collapse, vertex relocation.

References

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[4] O. Tasar, E. Maggiori, P. Alliez, and Y. Tarabalka. Polygonization of binary classification maps using mesh approximation with right angle regularity. In *IEEE IGARSS*, 2018.